Uncertain Shapelet Transform: A Shapelet-based Approach for Uncertain Time Series Classification

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October 11, 2019

Context: TransiXplore project

- Aims to study astronomical transient objects
- Objects are represented by their light curve
- Light curves are subject to uncertainty
- Uncertainty is explicitly expressed
- Physicists think that a shapelet-approach could work well

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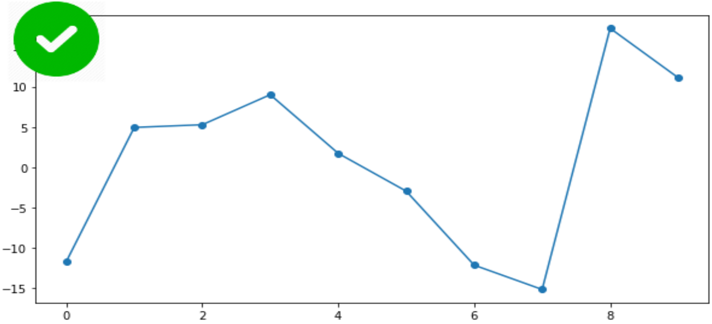
Introduction

- **Time series classification**: *classification* of objects modelized as *time series*. ex: Plasstic challenge
- **Time series**: sequence of chronologycal data
- Application: Physics, Medicine, Engineering, ...
- Very active field

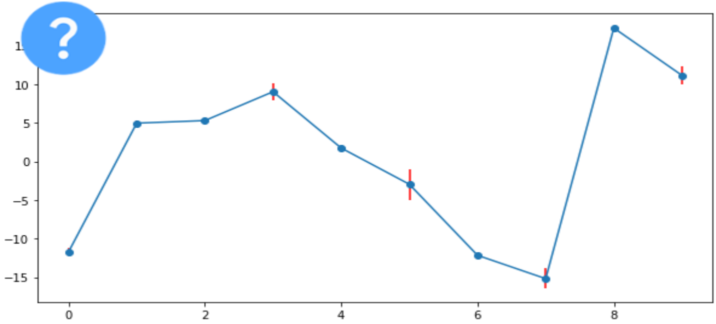
State of the art



Many classification methods

- Machine learning-based [Bagnall et al., 2017]: **Shapelet Transform**, BOOS, etc
- Deep learning-based [Fawaz et al., 2019b]: **ResNet**, FCN, etc
- Composition-based [Lines et al., 2018]: **HIVE-COTE**, FLAT-COTE

State of the art



No method found for uncertain time series, but we have

- Error analysis strategies [Taylor, 1996]
- Uncertain supervised classifiers: UDT[Tsang, Kao, Yip, Ho, and Lee, 2009]

Our motivation and method

Motivation

- Uncertainty cannot be eliminated [Taylor, 1996]
- Explicitly take uncertainty into account when it is available will lead to more accurate results

Method

1. Propagate uncertainty in shapelet transformation
2. Use an uncertain supervised classifier

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Time series

Time series (without uncertainty)

Sequence of m chronological values. m is the time series length.

$$T = \{t_1, t_2, ..., t_m\}$$

Uncertain time series

A time series where each value has an uncertainty. We represent uncertainty as follow.

$$x = x_{best} \pm \delta x$$

Subsequence

Sequence of l consecutive values of a time series starting at position i

$$S = \{t_{i+1}, ..., t_{i+l}\}$$

Notion of distance

Let $S = \{s_1, s_2, ..., s_l\}$ and $R = \{r_1, r_2, ..., r_l\}$ be two subsequences of same length l.

Distance between subsequences

$$\mathrm{ED}(S, R) = \frac{1}{l}\sum_{i=1}^{l}(s_i - r_i)^2.$$

Let $T = \{t_1, t_2, ..., t_m\}$ be a time series of length m, $m > l$

Distance between subsequence and time series

$$\mathrm{ED}(S, T) = \min\{\mathrm{ED}(S, R)\ \forall R \in T\}$$

Notion of separation

Le D be a set of time series

Separator

sp is a sperator of D if it divides D in two sets D_1 and D_2 such that

$$D_1 = \{T \mid \mathrm{ED}(T, sp) \leq \epsilon, \forall T \in D\},$$

$$D_2 = \{T \mid \mathrm{ED}(T, sp) > \epsilon, \forall T \in D\}, \epsilon \in R.$$

Information Gain

It is a measurement of the quality of a separator.

$$IG(D, sp) = H(D) - (\frac{|D_1|}{|D|}H(D_1) + \frac{|D_2|}{|D|}H(D_2))$$

$H(D)$ is the entropy on the dataset D

Notion of Shapelet

Horned Lezard and turtle can be differenciated by the presence of horns. No need to examine every part of the body.

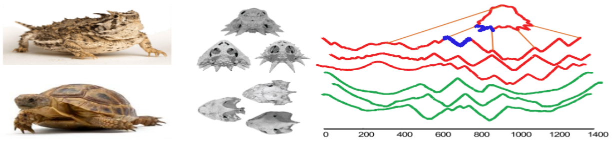

Figure 1: Horned Lizard vs Turtle.

Shapelet

It is a separator that maximizes the information gain.

$$S = \underset{sp}{\text{argmax}}(IG(D, sp))$$

Shapelet-based classification

General idea

Given a dataset of time series:

1. Select the first k shapelets
2. Compute feature vectors: vectors of distances to shapelets
3. train a classifier on the set of feature vector.

Advantages of shapelet-based classification

- Interpretability
- Robustness
- Rapid inference

Shapelet-based classification

Illustration

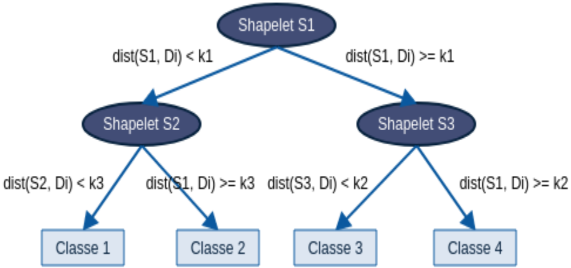

Figure 2: Shapelet decision tree illustration

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Uncertainty propagation techniques

Let $x = x_{best} \pm \delta x$ and $y = y_{best} \pm \delta y$. From the book "An Introduction to Error Analysis: The Study of Uncertainties in Physical Measurements" [Taylor, 1996] we have:

Addition and substraction

$$x + y = (x_{best} + y_{best}) \pm (\delta x + \delta y)$$

$$x - y = (x_{best} - y_{best}) \pm (\delta x + \delta y)$$

Multiplication and division

$$x \cdot y = (x_{best} \cdot y_{best}) \pm (\delta x \cdot |y_{best}| + \delta y \cdot |x_{best}|)$$

$$\frac{x}{y} = (\frac{x_{best}}{y_{best}}) \pm (\frac{\delta x \cdot |y_{best}| + \delta y \cdot |x_{best}|}{|y_{best}|^2})$$

Uncertain Euclidean Distance

Let $S \pm \delta S = < s_1 \pm \delta s_1, s_2 \pm \delta s_2, ..., s_l \pm \delta s_l >$ and $R \pm \delta R = < r_1 \pm \delta r_1, r_2 \pm \delta r_2, ..., r_l \pm \delta r_l >$ be two uncertain subsequences. If they were not uncertain, then ST algorithm would compute the distance between them as follow:

$$ED(S, R) = \frac{1}{l} \sum_{i=1}^{l} (s_i - r_i)^2$$

Using the previous propagation techniques we define **UED** as follow:

$$UED(S \pm \delta S, R \pm \delta R) = (\frac{1}{l} \sum_{i=1}^{l} (s_i - r_i)^2) \pm (\frac{2}{l} \sum_{i=1}^{l} |s_i - r_i| \times (\delta s_i + \delta r_i))$$

$$UED(S \pm \delta S, R \pm \delta R) = ED(S, R) \pm (\frac{2}{l} \sum_{i=1}^{l} |s_i - r_i| \times (\delta s_i + \delta r_i))$$

Ordering uncertain measures

Let $x = x_{best} \pm \delta x$ and $y = y_{best} \pm \delta y$, we have the following properties:

- $x = y$ if and only if $x_{best} = y_{best}$ and $\delta x = \delta y$
- $x < y$ if and only if one of the following conditions is satisfied:
  - $x_{best} < y_{best}$
  - $x_{best} = y_{best}$ and $\frac{\delta x}{x_{best}} < \frac{\delta y}{y_{best}}$

We can now define the uncertain distance between an uncertain time series $T \pm \delta T$ and a subsequence $S \pm \delta S$

Definition

Uncertain distance between time series and subsequence

$$UED(S \pm \delta S, T \pm \delta T) = \min\{UED(S \pm \delta S, R \pm \delta R)\ \forall R \pm \delta R \in T \pm \delta T\}$$

Uncertain data classification

Flat representation

- Represent each uncertain data by a flat vector
- The first half of the vector contains best guesses and the second half contains uncertainties

Illustration

T: an uncertain time series
X: $[udist_1, udist_2, ..., udist_k]$, where
$udist_j = UED(T, shapelet_j) = d_j \pm \delta d_j$, then:

$$Flat(X) = [d_1, d_2, ..., d_k, \delta d_1, \delta d_2, ..., \delta d_k]$$

Uncertain data classification

Flat Classification of uncertain time series

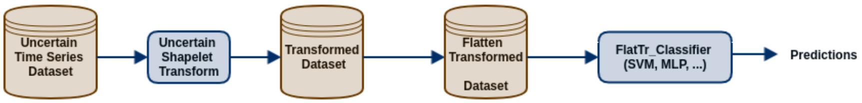


Figure 3: Flat classification archtecture

Pros

- Simplicity
- Uncertainty is taken into account through all the process

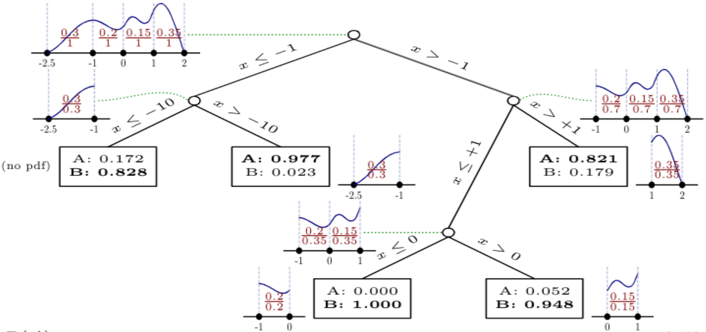
Cons

- Risk of having large flattened vectors.
- The classifier used (FlatTr_Classifier) is not aware of uncertainty

Uncertain data classification

Uncertain decision tree classifier: an Overview

- Proposed by Tsang et al. [2009]
- Awared of uncertainty in data



$$P(A) = 0 \times 0.172 + 0.3 \times 0.977 + 0.2 \times 0.0 + 0.15 \times 0.052 + 0.35 \times 0.821 = 0.59$$
$$P(B) = 0 \times 0.828 + 0.3 \times 0.023 + 0.2 \times 1.0 + 0.15 \times 0.948 + 0.35 \times 0.179 = 0.41$$

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Data source

- We used 21 datasets from UEA/UCR: `http://www.timeseriesclassification.com/dataset.php`
- These datasets do not have uncertainty

Uncertain datasets are obtained by adding generated uncertainty to each dataset. The generated uncertainty follows a zero-mean normal distribution.

Source code

- Written in JAVA
- Extends the UEA/UCR time series classification source code
- Available on Github:
  https://github.com/frankl1/Uncertain-Shapelet-Transform

Results

Accuracy comparison

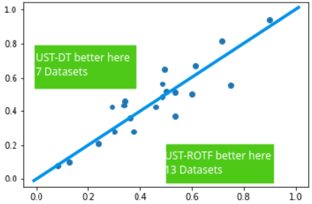

Figure 4: UST-DT vs UST-ROTF

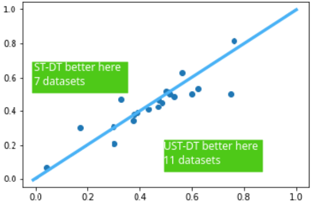

Figure 5: ST-DT vs UST-DT

- From figure 4 $\rightarrow$ Classifier matter
- From figure 5 $\rightarrow$ Handling uncertainty matter

Results

Underfitted datasets

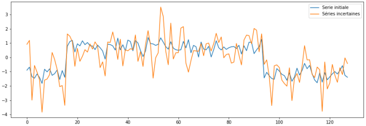

Figure 6: An instance from CBF

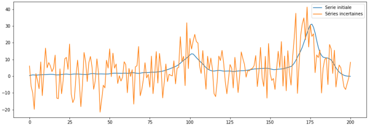

Figure 7: An instance from Fungi

- Generated uncertainty is very high
- Time series classifiers are **Very sensitive** to adversarial attack [Fawaz et al., 2019a; Karim et al., 2019]

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Conclusion

What we did

- We explored how to classify uncertain time series
- We proposed Uncertain Shapelet Transformation, which shown interesting results

What we will do

- Use a supervised classifier that is aware of uncertainty, for instance UDT[Tsang et al., 2009]
- Evaluate UST on a real uncertain datasets: TransiXplore data
- Evaluate UST on the remaining 117 UEA/UCR datasets

References I

A. Bagnall, J. Lines, A. Bostrom, J. Large, and E. Keogh. The great time series classification bake off: a review and experimental evaluation of recent algorithmic advances. *Data Mining and Knowledge Discovery*, 31 (3):606–660, 2017.

M. Dallachiesa, B. Nushi, K. Mirylenka, and T. Palpanas. Uncertain Time-Series Similarity: Return to the Basics. *arXiv e-prints*, art. arXiv:1208.1931, Aug 2012.

H. I. Fawaz, G. Forestier, J. Weber, L. Idoumghar, and P.-A. Muller. Adversarial attacks on deep neural networks for time series classification, 2019a.

H. I. Fawaz, G. Forestier, J. Weber, L. Idoumghar, and P.-A. Muller. Deep learning for time series classification: a review. *Data Mining and Knowledge Discovery*, 33(4):917–963, 2019b.

References II

J. Grabocka, N. Schilling, M. Wistuba, and L. Schmidt-Thieme. Learning time-series shapelets. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 392–401. ACM, 2014.

J. Hills, J. Lines, E. Baranauskas, J. Mapp, and A. Bagnall. Classification of time series by shapelet transformation. *Data Mining and Knowledge Discovery*, 28(4):851–881, 2014.

F. Karim, S. Majumdar, and H. Darabi. Adversarial attacks on time series, 2019.

J. Lines, S. Taylor, and A. Bagnall. Time series classification with hive-cote: The hierarchical vote collective of transformation-based ensembles. *ACM Trans. Knowl. Discov. Data*, 12(5):52:1–52:35, July 2018. ISSN 1556-4681.

References III

T. Rakthanmanon and E. Keogh. Fast shapelets: A scalable algorithm for discovering time series shapelets. In *proceedings of the 2013 SIAM International Conference on Data Mining*, pages 668–676. SIAM, 2013.

V. S. Siyou Fotso, E. Mephu Nguifo, and P. Vaslin. Frobenius correlation based u-shapelets discovery for time series clustering. Apr. 2018. working paper or preprint.

J. R. Taylor. *An Introduction to Error Analysis: The Study of Uncertainties in Physical Measurements*. University Science Books, 2 sub edition, 1996.

S. Tsang, B. Kao, K. Y. Yip, W.-S. Ho, and S. D. Lee. Decision trees for uncertain data. *IEEE transactions on knowledge and data engineering*, 23(1):64–78, 2009.

References IV

L. Ye and E. Keogh. Time series shapelets: a new primitive for data mining. In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 947–956. ACM, 2009.

Thanks for your attention !